Temporal Payment Issues in Contingent Valuation Analysis

Craig A. Bond
Department of Agricultural and Resource Economics
University of California, Davis
Davis, CA 95616
bond@primal.ucdavis.edu

Kelly Giraud
Department of Resource Economics and Development
University of New Hampshire
Durham, NH 03824
giraud@unh.edu

Douglas Larson
Department of Agricultural and Resource Economics
University of California, Davis
Davis, CA 95616
larson@primal.ucdavis.edu

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Abstract: We analyze agent response to disparate payment schedules for protection of critical habitat units for the Seller sea lion in Alaska. The model allows for identification of implicit and explicit discount rates using information from a system of maximum likelihood equations. Testing is done using data for one, five, and fifteen year payment treatments.

The temporal treatment of payment schedules in stated preference applications is a subject to be taken seriously by researchers attempting to value willingness to pay (WTP) for non-market goods. Much research has been directed towards sequencing and scope issues, as well as the properties of alternative payment mechanisms (Carson, 1997). Many of these studies pay particular attention to incentive structures inherent in the survey design, yet relatively little has been written about the time preference for payments of environmental goods. Especially when the program in question provides a pure public good, likely financed by tax dollars, it seems inappropriate to frame a dichotomous choice question in terms of a one-shot, lump-sum payment, when the true payment vehicle would likely be a stream of payments over time. Similarly, analysis of the benefits of the program should incorporate the temporal dimensions of the benefits stream, especially if the time periods differ between the two.

Much of the literature that does, in fact, mention bid treatment over time looks at sensitivity of summary measures of willingness to pay for a particular good or set of goods across the treatments. It was found that in eliciting willingness to pay for a toxic waste treatment facility in British Colombia, for example, respondents as a group did not distinguish between payment schedules of one and five years (Kahneman and Knetsch, 1992), violating the standard economic assumption of a positive discount rate. Expanding this idea, Stevens, DeCoteau, and Willis (1997) compared both scale and temporal embedding effects for both a public good (salmon restoration) and a private good (movie passes at a local theatre), and concluded that responses are not invariant to payment schedule. The authors also indicated in a footnote that an implicit assumption about the length of time the program provides benefits is necessary if one is to assume implicit discount rates from mean WTP estimates. Both of these studies used open-ended elicitation methods, with Kahneman and Knetsch conducting phone interviews and Stevens, et. al. collecting their data via a questionnaire.

Strumborg, Baerenklau, and Bishop (2001) studied temporal payment mechanism response in a contingent valuation study of Lake Mendota in Wisconsin, which elicited responses via a mail survey with a modified payment card and randomly split the sample into three and ten year treatment groups, with program benefits explicitly capped at ten years. They found that, if market discount rates are assumed, the ten-year subsample yields net present values that are higher than the three-year subsample.[1] Chavas and Mullarkey (2002) develop a model of valuation under temporal future learning uncertainty and irreversibility in the policy decision arena. They find that in the face of temporal uncertainty, there is a risk premium that is added to the willingness to pay for the option value of a natural resource. It seems logical that the higher the level of uncertainty, the larger the risk premium. Following this logic, it may be the case the risk premium may be higher for projects that extend further into the future because of the future learning that occurs with the resource under consideration. In other words, there may be a risk premium that has a negative correlation with future discounting because of uncertainty and irreversibility of the resource change. Finally, van der Pol and Cairns (2001) used discrete choice data to calculate implicit discount rates for health by collecting multiple data points on each respondent, and found that discounting varied by certain demographic and elicitation method characteristics.

This paper extends the line of research by analyzing agent response to payment schedule for a pure public good, protection of critical habitat units for the Steller sea lion

[1] The authors incorporated a discount rate of 4% into their regression equations.

in Alaska that generates an infinite stream of benefits over the life of the program. We proceed as follows: the next section develops the theoretical model, which allows for estimation of explicit discount rates through normalization to the one-year responses. The model is then tested using the Steller sea lion dataset by calculating implicit discount rates from mean willingness to pay across two additional payment horizons. Next, the explicit discount rates are estimated for those subsamples that exhibit significant differences in slope coefficients across treatments. Finally, we discuss the implications for future research and analysis.

THEORETICAL MODEL

Suppose an independent sample of respondents is presented with a survey which solicits willingness to pay for a public program with different repayment periods. Specifically, individual i is asked whether s/he is willing to pay B_i dollars per year for n_i years for the provision of the public program. If the program is supplied, it provides a stream of benefits over an infinite time horizon.[2] As the program embodies costs and benefits over time, any expression for WTP necessarily embodies the individual's discount rate. Thus, we model the program choice as a comparison between the net present values (NPV) of the payments stream and the benefits stream.

The (finite) payment stream can be expressed as the difference between two infinite streams; one beginning in year 0, and the other beginning in year n_i-1. Assuming a discount rate r, the NPV of the infinite stream B_i beginning now is

$$PV_0^{\infty}(B_i) = B_i + \frac{1}{(1+r)} B_i + \frac{1}{(1+r)^2} B_i + \ldots$$

[2] More generally, the benefit stream accrues over a period different than the repayment period.

and

$$\frac{1}{(1+r)}\,PV_0^{\infty}(B_i) = \frac{1}{(1+r)}\,B_i + \frac{1}{(1+r)^2}\,B_i + \frac{1}{(1+r)^3}\,B_i + \ldots$$

so that

$$PV_0^{\infty}(B_i)\left(1 - \frac{1}{(1+r)}\right) = B_i$$

or

$$PV_0^{\infty}(B_i) = B_i \cdot \frac{1+r}{r}. \tag{1}$$

Similarly, an infinite stream of payments beginning n_i years from now is worth

$$PV_n^{\infty}(B_i) = \frac{1}{(1+r)^{n_i}}\,PV_0^{\infty}(B_i)$$

$$= \frac{1}{(1+r)^{n_i}}\,B_i \cdot \frac{1+r}{r}$$

$$= \frac{1}{(1+r)^{n_i - 1}}\,B_i \cdot \frac{1}{r}\ . \tag{2}$$

Subtraction of (2) from (1) yields the NPV to individual i of a finite stream of payments beginning now and ending in year n_i-1:

$$PV_n(B_i) = PV_0^{\infty}(B_i) - PV_n^{\infty}(B_i)$$

$$= (B_i) \cdot \frac{1+r}{r}\left(1 - \frac{1}{(1+r)^{n_i}}\right). \tag{3}$$

Assuming the annual benefit received by the individual is given by the measure WTPi, and the benefits accrue over an infinite time horizon, the NPV of the benefit stream is given by $\frac{\text{WTP}_i}{r}$. Thus, when faced with the hypothetical question of paying B_i dollars per year for n_i years for the program, the respondent votes yes so long as the NPV of benefits is at least equal to the NPV of the payment stream given by (3).

Of course, the researcher does not observe the true WTP_i as it is a latent variable. Instead, we define y_i as an observable binary variable with the following properties:

$$y_i = 1 \text{ if } \frac{WTP_i}{r} \geq PV_n(B_i)$$

$$y_i = 0 \text{ if } \frac{WTP_i}{r} < PV_n(B_i)\ . \tag{4}$$

Assuming that the true data generating process for annual individual benefits is $WTP_i = X_i\beta + \sigma\varepsilon_i$, where $\varepsilon_i \sim N(0,1)$,[3] the probability of observing a "no" response from an individual facing bid B_i^n can be written as

$$\text{Prob}\{y_i = 0\} = \text{Prob}\left\{\frac{WTP_i}{r} < NPV(B_i^n)\right\}$$

$$= \text{Prob}\left\{\frac{X_i\beta}{r} + \left(\frac{\sigma}{r}\right)\varepsilon_i < \frac{B_i^n}{r}\cdot\delta(r,n_i)\right\}, \tag{5}$$

where for simplicity, $\delta(r,n_i) \equiv \left(1 + r - \frac{1}{(1+r)^{n_i-1}}\right)$. Note that the probability statement in (5) is a straightforward generalization of Cameron (1988), explicitly taking the time dimensions of the payment and benefit streams into consideration. Isolating B_i^n then yields

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[3] Although this model assumes a single-index linear specification, generalization to non-linear functional forms is straightforward. Similarly, non-normal errors could be assumed.

$$\text{Prob}\left\{\frac{\text{WTP}_i}{r} < \text{NPV}(\text{B}_i^n)\right\} = \text{Prob}\left\{\frac{\text{X}_i\beta}{\delta(r,n_i)} + \left(\frac{\sigma}{\delta(r,n_i)}\right)\varepsilon_i < \text{B}_i^n\right\}, \tag{6}$$

which illustrates the fact that it is impossible to estimate β, σ, and r separately without some sort of normalization.

Note that in the absence of the discount factor, the presence of the annual bid B_i^n would permit identification of the β coefficient vector, allowing for calculation of the scale of WTP directly from the latent variable formulation. While this is not be possible here, as there are three parameters of interest, it is nonetheless possible to identify the discount rate r and β up to a scale σ, as is typical in standard logit and probit analysis, by normalization of the variance parameter to 1. Cameron's approach, therefore, can be used to identify exactly one additional parameter of interest, although doing so results in limiting oneself to speaking in terms of probabilities without additional assumptions on scale.[4]

An alternative strategy, assuming at least two payment periods, is to normalize the parameter vector by r in estimation, thereby allowing for identification of location, scale, and the discount rate. This normalization allows the system of equations to be written such that one equation identifies location and scale, while the others identify r. Estimation then yields estimates of both r and the normalized parameters, from which the underlying parameter vectors can be recovered.

To illustrate the process, write (5) as

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[4] Of course, this does not preclude using methods such as the familiar approach popularized by Hanneman (1984) to estimate mean WTP.

$$\text{Prob}\left\{\frac{\text{WTP}_i}{r} < \text{NPV}(\text{B}_i^n)\right\} = \text{Prob}\left\{\text{X}_i\beta^* + \sigma^*\,\varepsilon_i < \frac{\text{B}_i^n}{r}\cdot\delta(r,n_i)\right\}, \tag{7}$$

where $\beta^* = \beta/r$ and $\sigma^* = \sigma/\text{r}$, and assume that we have data for two time treatments, $n1 = 1$ and $n2 > 1$. Then the probability of a no response for individuals asked to pay over the two time streams can be expressed as

$$\text{Prob}\left\{\frac{\text{WTP}_i}{r} < \text{NPV}(\text{B}_i^1)\right\} = \text{Prob}\left\{\text{X}_i\beta^* + \sigma^*\,\varepsilon_i < \text{B}_i^1\right\} \tag{8}$$

$$\text{Prob}\left\{\frac{\text{WTP}_i}{r} < \text{NPV}(\text{B}_i^n)\right\} = \text{Prob}\left\{\text{X}_i\beta^* + \sigma^*\,\varepsilon_i < \frac{\text{B}_i^n}{r}\cdot\delta(r,n_i)\right\}, \tag{9}$$

making use of the fact that $\delta(r,1) = r$. Again isolating the annual bid payment, the system defined by (8) and (9) can be rewritten as

$$\text{Prob}\left\{\frac{\text{WTP}_i}{r} < \text{NPV}(\text{B}_i^1)\right\} = \text{Prob}\left\{\text{X}_i\beta^* + \sigma^*\,\varepsilon_i < \text{B}_i^1\right\} \tag{8'}$$

$$\text{Prob}\left\{\frac{\text{WTP}_i}{r} < \text{NPV}(\text{B}_i^n)\right\} = \text{Prob}\left\{\text{X}_i\beta^*\cdot\frac{\text{r}}{\delta(r,n_i)} + \sigma^*\cdot\frac{\text{r}}{\delta(r,n_i)}\,\varepsilon_i < \text{B}_i^n\right\} \tag{9'}$$

or equivalently as

$$\text{Prob}\left\{\frac{\text{WTP}_i}{r} < \text{NPV}(\text{B}_i^1)\right\} = \text{Prob}\left\{\text{X}_i\beta_1^* + \sigma_1^*\,\varepsilon_i < \text{B}_i^1\right\} \tag{8''}$$

$$\text{Prob}\left\{\frac{\text{WTP}_i}{r} < \text{NPV}(\text{B}_i^n)\right\} = \text{Prob}\left\{\text{X}_i\beta_2^* + \sigma_2^*\,\varepsilon_i < \text{B}_i^n\right\} \tag{9''}$$

Clearly, (8'') and (9'') can be estimated by standard maximum likelihood procedures, although this in itself does nothing to identify the extra parameter. However, comparing (9') to (8') suggests that we can use the one-year treatment to identify β^* and σ^*, and differences in the parameters from (8'') to (9'') are due solely to the discount factor. For a given r = r, then, one could test the hypothesis

$$H_0 : \beta_2^* = \beta_1^* \cdot \frac{\mathrm{r}}{\delta(r,n_i)}, \quad \sigma_2^* = \sigma_1^* \cdot \frac{\mathrm{r}}{\delta(r,n_i)},$$

which would identify a range of r for which the data do not reject the hypothesis that r = r.

This methodology can be extended to directly estimate all of the parameters, including r, using equations (8') and (9') and restricting the parameter vectors to be identical, thus embodying the assumption that the same parameter vectors characterize annual WTP, and differences in the estimated coefficients are due to the discount factor alone. The log likelihood function can be developed by rewriting (9') so that

$$\mathrm{Prob}\{\mathrm{y}_i = 0\} = \mathrm{Prob}\left\{\varepsilon_i < \frac{-\,\mathrm{X}_i\beta^*}{\sigma^*} + \frac{\mathrm{B}_i^n}{\sigma^*} \cdot \frac{\delta(r,n_i)}{\mathrm{r}}\right\} \tag{10}$$

Assuming normal errors, taking logs, and summing over the sample, the log likelihood function becomes

$$\log \mathrm{L} = \sum_{\mathrm{i}=1}^{\mathrm{N}} \{\mathrm{y}_i \ln [1 - \Phi(-\,\mathrm{X}_i\beta^*/\sigma^* + \mathrm{B}_i^n/\sigma^* \cdot \delta(r,n_i)/\mathrm{r})]$$

$$+ (1 - \mathrm{y}_i) \ln [\Phi(-\,\mathrm{X}_i\beta^*/\sigma^* + \mathrm{B}_i^n/\sigma^* \cdot \delta(r,n_i)/\mathrm{r})]\} \tag{11}$$

Optimization of (11) by standard numerical procedures, such as the MAXLIK option in

GAUSS, is straightforward, and asymptotic standard errors for the parameter estimates will be correct so long as the density is correctly specified. The usual hypothesis tests can then be performed to empirically investigate a number of issues regarding intertemporal preferences within a CVM framework, including sensitivity of responses to the temporal payment schedule and testing if rates of time discount are significantly different from zero. In addition, one can extend the model to allow for endogenous variation in the discount rate parameter r over individuals, simply by specifying an appropriate functional form for $r(z)$, such as the linear $r(z) = z'\gamma + \varepsilon_i$, where z is an n x k subset of the exogenous regressor set x. Through this specification, we can test for significant differences in the discount rate between categories of respondents.

SURVEY AND DATA

Giraud and Turcin (2001) collected referendum data on willingness to pay for a proposed expanded federal Steller sea lion recovery program off the coast of Alaska. This program consisted of increased restrictions on commercial fishing activity within the certain designated buffer zones around critical habitat units for the Steller sea lion, as well as a doubling of funding for research efforts to understand the ongoing population decline. Data was collected using the Dillman Tailored Design Method (2001) via a questionnaire that was mailed to a random sample of 1,000 households in each of three regions: the Alaskan Boroughs that contain the critical habitat and buffer zones, the state of Alaska, and the United States as a whole. After describing the relevant background information, assessing the respondent's views on endangered species management, and evaluating familiarity with the Steller sea lion and the associated fishery, the survey presented each agent with the following dichotomous choice question:

> "If the Expanded Federal Steller Sea Lion Recovery Program was the only issue on the next ballot and it would cost your household $____ in additional Federal taxes every year for the next ____ year(s), would you vote in favor of it? (By law the funds could *only* be used for the Steller sea lion program."

Bid amounts for each of the three stratifications varied from $1 to $350, a range established by extensive use of focus groups and pre-testing. In addition to the varying bid amounts, there were also three temporal treatments of one, five, and fifteen years. Each respondent was asked to vote only once, and associated demographic information was collected at the end of the survey. A summary of the geographically pooled data used for analysis for each of the three temporal treatment groups is presented in Table 1.

EMPIRICAL RESULTS

Before proceeding directly to the discount model, it is useful to examine the results from the prototypical lump-sum payment vehicle model, which in the current context assumes $n_i = 1$. Separate coefficients were estimated for each of the three geographic subsamples, and the results are reported in Table 2. Due to the linear functional form of the data generating process, the β coefficients give the marginal change in WTP for a one-unit change in each regressor, identified only up to location and scale, with no information regarding the temporal preferences of the agents.

For each subsample, *ProSpec* and *ProJobs* have the largest t-statistics of the explanatory variables, and are of the expected sign[5]. These variables measure the generalized preferences of the respondents towards the major competing uses of the

[5] It should be again noted that reported standard errors are computed from the inverse Hessian and are asymptotic in nature. All hypothesis tests using these standard errors, then, implicitly assume $n \rightarrow \infty$.

critical habitat units (endangered species protection versus commercial fishery activity and employment, respectively) via a non-consecutive series of three Likert-scale[6] questions at the beginning of the survey. In addition, it has been argued that prior knowledge can influence WTP (Giraud, et al., 1999), so binary variables for those respondents who indicated they had "read or heard anything" about the endangered Stellar sea lion (*KnowSSL*) or Alaskan coastal villages (*KnowVil*) are included as explanatory variables in each model. The significance of each, however, tends to decline as familiarity with the issue increases, as residents of Alaska were inundated with information regarding this highly contentious program. The coefficients on the indicator variable for *Gender* (Female = 1) and on the coefficient of *Member*, an indicator variable designating membership in an environmental organization, are marginally significant in at least one of the models, and are maintained throughout the paper. Despite the relatively large standard errors on the slope coefficients, perhaps a result of the small sample size resultant from the geographic stratification, the regressions as a whole are significant using a likelihood ratio test.

The next step in the procedure is to estimate the remaining equations in each system, as in equations (9') and (9'') above. For this data set, this implies two additional equations for each geographic subsample, corresponding to the five-year and fifteen-year payment treatments. This provides information regarding the size of the discount rate r, as we use the relationship between the slope coefficients to provide point estimates of the parameter. As can be seen through manipulations of the above equations, the predicted net present value of willingness to pay over the infinite time horizon for, say, the 5 year treatment is

[6] The scale ranges from Strongly Disagree = 1 to Neutral = 3 to Strongly Agree = 5.

$$\frac{\overline{\mathrm{WTP}_5}}{r} = \frac{1}{\mathrm{N}_5}\sum_{i=1}^{\mathrm{N5}} \mathrm{X}_i\beta_2^* = \frac{1}{\mathrm{N}_5}\sum_{i=1}^{\mathrm{N5}} \mathrm{X}_i\beta^* \cdot \frac{\mathrm{r}}{\delta(r,n_5)}\,, \tag{12}$$

where N_5 is the number of observations in the particular five year treatment. Similarly, predictions for the one year treatment are

$$\frac{\overline{\mathrm{WTP}_1}}{r} = \frac{1}{\mathrm{N}_1}\sum_{i=1}^{\mathrm{N1}} \mathrm{X}_i\beta^*\,. \tag{13}$$

As the sample size becomes large, and assuming that differences in willingness to pay are solely the result of discounting, substitution of (13) in (12) yields

$$\mathrm{NPV}\ \overline{\mathrm{WTP5}} = \mathrm{NPV}\ \overline{\mathrm{WTP1}} \cdot \frac{\mathrm{r}}{\delta(r,n_5)}\,, \tag{14}$$

with the bar denoting the mean. Equation (14) can be solved to provide implicit estimates of r, much as the previous literature has done.

The equations and estimates of willingness to pay and implicit discount rates are reported in Tables 3 and 4 for each of the subsamples and temporal treatments. We reject a zero willingness to pay only for the one and five year treatments in the Rest of U.S., the geographic difference explained primarily by the fact that a very high percentage of Alaskan residents are economically tied to the local fisheries relative to the rest of the United States through either themselves or family members. As such, protection of the habitat units may, in fact, constitute a “bad” rather than a good for many respondents, and their compensating variation may be negative. Comments received in focus groups, pre-testing and on the survey itself indicate that some respondents viewed sea lions as a pest. Others thought that previous efforts by the government to protect the sea lion were unsuccessful and so the protection program should not continue.

The temporal dimension of estimated WTP across the subsamples is intriguing as well. A priori, we expect mean $X_i\beta^*$ to be largest for the one year treatment and decline with the length of the payment horizon, in accordance with equation (9'). However, only the Rest of Alaska exhibits this pattern, and does so with the fifteen year point estimate turning negative, perhaps as a result of the aforementioned geographic effect.[7] The Rest of U.S. sample displays a higher value for the five year treatment than the one year, and the Boroughs sample switches the expected relationship between the five and fifteen year values. Undoubtedly, much of this effect is due to noise in the data and marginal explanatory power of the overall explanatory variables for this particular problem. Nevertheless, Table 4 shows that, at least for those not living in the Boroughs portion of Alaska, there is a definite tendency in the respondents towards distinguishing between the one year and fifteen year payment periods, but it is not as strong for the one and five year periods. Essentially, this conforms to earlier empirical findings in previous work (Stevens, DeCoteau, and Willis, 1997; Stumborg, Baerenklau, and Bishop, 2001; van der Pol and Cairns, 2001).

With these results in mind, we now move to explicit estimation of the discount rates, as given by maximization of the likelihood given by equation (11). Of course, in order to estimate any additional parameter, in this case, r, with a relative degree of efficiency, there must be variation between the unrestricted coefficient estimates reported in Tables 2 and 3 and a restricted model which forces these coefficients to be equal. If

[7] As is typical with contingent valuation analysis, the standard errors on WTP are large, and one cannot statistically reject equivalence of WTP for any temporal treatment within any one geographic group. In this particular case, the stratification greatly reduces degrees of freedom, further aggravating the problem.

this is not the case, then the data suggests that $\frac{r}{\delta(r,n_i)} = 1$, and there is no way to identify the rate of time preference using the methodology described in this paper. As such, the method itself will perform most adequately with large samples of well-behaved data, with relatively precise coefficient estimates.

Likelihood ratio tests on the Steller sea lion data confirm the fact that this sample does not have many of the desired properties necessary for efficient estimates of the discount parameter r. Three of the six tests (including both for the Boroughs subsample) provide evidence that the restrictions are not binding, and thus the slope coefficients are not jointly significantly different between the one year and multiple year treatments, preventing explicit estimation of the discount rates. The remaining three equations are reported in Table 5.

Of the three estimated discount parameters, only one, for the Rest of Alaska sample, one vs. fifteen year treatment, is significantly different from zero, yet the sign is an infeasible -.74. The reader, however, will recall that the willingness to pay calculated in Table 4 changes sign from the one year to the fifteen year treatment, explaining the negative parameter estimate.

While the remaining estimates are asymptotically significant only at a low level of confidence for the individual r parameters, a likelihood ratio test can be performed to assess if the model including the discount rate explains the data as well as a completely unrestricted model. In the case of the Rest of Alaska, one vs. five year treatment, we reject the null hypothesis that the restricted discount model performs as well as the unrestricted, with a test statistic of 17.6. This result suggests that features of the data other than discounting account for the differences in the parameter estimates. One possible explanation is that the sample is that the special population of Alaska is bifurcated into those with especially strong preferences towards environmental quality, and those whose preferences are the polar opposite and whose livelihoods and economic security are directly impacted by the fishery, leading to heterogeneity of parameters within the sample that cannot be explained by time preferences alone.

The parameter estimate for the discount rate for the Rest of U.S, one vs. fifteen year treatment, is thus the only endogenously estimated r which is reasonable in both sign and magnitude, and explains the data as well as a completely unrestricted model. The implicit discount rate calculated for this subsample was .39, while the explicit point estimate is a slightly higher .48. Recovery of the true beta parameters (denoting the change in annual willingness to pay given a change in the regressor) using simple point estimates yields high annual marginal effects of $238.84 for *ProSpec*, $238.25 for *ProJobs*, and $215.10 for *KnowSLL*.

DISCUSSION AND IMPLICATIONS

The implicit discount rates from mean willingness to pay are quite high relative to market rates, but in line with those found by Stevens, DeCoteau, and Willis (1997) and Stumborg, Baerenklau, and Bishop (2001). Similarly, the results from the Rest of U.S. subsample match the Kahneman and Knetsch (1992) finding that five year intervals make little difference in estimated mean willingness to pay. However, when attempting to measure *explicit* discount rates for those subgroups for which it is possible under this methodology, we find that a positive discount rate is observed only at a low level of statistical significance, and does not always explain the data as well as a model with separate coefficients for each temporal treatment.

The relatively small sample size and resultant inefficiency of parameter estimates is one explanation for this finding, and further research is necessary to test the applicability of this method to other data sets. We hypothesize that models that perform relatively better explaining the data and with larger sample sizes will have more success applying this method; for example, the efficiency gains using double-bounded instead of single-bounded elicitation methods may be utilized to further pinpoint the discount parameter estimates.

More generally, these results suggest that respondents are, in fact, sensitive to temporal payment schedules in a discrete choice format, at least in the long run. We further hypothesize that temporal embedding, as originally termed by Kahneman and Knetsch (1992), may be commodity, survey, or even time specific. It seems clear that across the CV research to date, as in the marketable goods case, there is little empirical support for the theoretical argument that agents discount money streams at the market rate of interest. This raises important questions about the proper treatment of benefits in a public policy context when considering projects with a temporal component, as typically researchers and decision-makers compare net present values of benefits versus costs when making their recommendations or decisions.

Finally, as previously noted, expansion of the model to allow for the discount rate parameter to be a function of regressors would be straightforward, presuming one achieves given sufficient variation in the slope parameters. Van der Pol and Cairns (2001), for example, found that discount rates tend to increase with increasing age, while

Thaler (1981) found a negative relationship between dollar sums and discount rates. Furthermore, Stevens, DeCoteau, and Willis (1997) suggest that budget constraints may play a role in determining discount factors. One could, in principle, choose a functional form for these explanatory variables and let $r = f(\gamma \mid X_i)$, thus allowing the discount rate to differ between individuals.

CONCLUSIONS

This paper introduced a model that allowed for explicit calculation of discount rate parameters given alternative temporal treatments of the bid vehicle in a contingent valuation context, along with a theoretical justification of calculation of implicit rates of discount using mean willingness to pay. Results suggest that respondents are more sensitive to payment period variation in the long run, and rates of discount are significantly higher than the market rate of interest. These findings are especially relevant with regards to pure public goods, such as the protection of endangered species, as recovery programs may often take many years and are unlikely to be financed with a lump-sum payment vehicle. Proper experiment design and execution, therefore, requires serious consideration of temporal payment issues in order to credibly present respondents with a realistic vehicle and to provide researchers with the proper information necessary to inform and advise policy makers.

Table 1: Summary Statistics - Dependent and Independent Variables

	Vote	*Bid*‡	*ProSpec*	*ProJobs*	*KnowSSL*	*KnowVil*	*Gender*	*Member*	*Age*	*Inc*†
One Year	0.47	0.83	3.66	3.05	0.68	0.75	0.24	0.12	49.41	68.76
n = 428	(0.50)	(1.03)	(1.03)	(1.11)	(0.47)	(0.43)	(0.43)	(0.32)	(12.55)	(41.32)
Five Year	0.49	0.80	3.68	2.75	0.66	0.72	0.27	0.15	49.43	65.13
n = 391	(0.50)	(1.05)	(1.01)	(0.61)	(0.48)	(0.45)	(0.45)	(0.35)	(13.38)	(37.22)
Fifteen Year	0.38	0.76	3.61	2.76	0.69	0.78	0.23	0.14	49.61	73.81
n = 385	(0.49)	(1.01)	(1.06)	(0.59)	(0.46)	(0.42)	(0.42)	(0.35)	(12.96)	(44.32)

‡ Measured in \$00. †Measured in \$000. Standard Errors in parentheses.

Table 2: Estimation Results, One Year Temporal Treatment

	Rest of U.S.	***Rest of AK***	***AK Boroughs***
ProSpec	103.1	286.3	245.3
	(44.92)	(149.8)	(181.8)
	2.295	1.911	1.349
ProJobs	-98.7	-80.66	-368.1
	(42.31)	(63.71)	(268.3)
	-2.332	-1.266	-1.372
KnowSSL	103.3	145.6	-108
	(71.01)	(147.1)	(216.4)
	1.455	0.9894	-0.4993
KnowVil	-56	-262.8	-266.9
	(57.78)	(190.8)	(303.3)
	-0.9691	-1.377	-0.88
Gender	23.44	296.3	223.4
	(59.37)	(182.5)	(237.)
	0.3948	1.624	0.9427
Member	30.78	-353.4	-307.3
	(118.4)	(235.5)	(286.8)
	0.26	-1.5	-1.071
Constant	-28.89	-605.1	509.6
	(205.4)	(457.5)	(614.4)
	-0.1407	-1.323	0.8294
σ	182.6	327.9	583.4
	(51.58)	(157.2)	(412.4)
	3.54	2.086	1.415
Log Likelihood	-104.6	-114.6	-152.1
n	112	142	174

Standard errors in parentheses, followed by t-stats.

Table 3: Estimation Results, Five and Fifteen Year Treatments

	Rest of U.S.		***Rest of AK***		***AK Boroughs***	
	Five	*Fifteen*	*Five*	*Fifteen*	*Five*	*Fifteen*
Prospec	145.3	107.7	243	92.11	167	173.1
	(54.42)	(27.92)	(91.28)	(32.25)	(72.03)	(58.13)
	2.671	3.856	2.662	2.857	2.319	2.979
Projobs	-175.5	-170.4	-220.8	-54.85	-176.9	-69.29
	(78.29)	(46.19)	(93.45)	(40.31)	(85.46)	(53.01)
	-2.242	-3.69	-2.363	-1.361	-2.071	-1.307
KnowSSL	93.01	110.9	-63.98	-13.13	67.76	39.59
	(93.42)	(60.12)	(99.58)	(45.93)	(102.3)	(82.78)
	0.9956	1.844	-0.6425	-0.2859	0.6626	0.4783
KnowVil	-130.7	64.54	165.1	2.918	-15.55	-74.21
	(93.56)	(46.87)	(145.7)	(70.69)	(111.1)	(91.84)
	-1.397	1.377	1.133	0.04127	-0.14	-0.808
Gender	-49	82.69	64.97	-1.138	-19.67	37.58
	(69.48)	(48.82)	(90.04)	(53.46)	(76.2)	(63.92)
	-0.7051	1.694	0.7215	-0.02129	-0.2581	0.5879
Member	-48.66	-102.2	38.5	-7.645	-77.54	26.72
	(91.83)	(75.16)	(108.3)	(48.97)	(103.1)	(82.68)
	-0.5299	-1.359	0.3556	-0.1561	-0.7519	0.3232
One	58.83	13.42	-329.5	-189	-131.9	-419.6
	(180.9)	(127.3)	(302.4)	(165.1)	(274.9)	(258.)
	0.3253	0.1055	-1.09	-1.145	-0.4798	-1.626
σ	233.1	115.6	254.2	124.4	271.2	226.1
	(82.33)	(28.4)	(91.53)	(37.6)	(102.1)	(70.61)
	2.831	4.071	2.778	3.307	2.656	3.202
Log Likelihood	-104.6	-83.72	-114.6	-113.3	-152.1	-156.1
n	112	97	139	127	141	161

Standard errors in parentheses, followed by t-stats.

Table 4: Mean Net Present Value Willingness to Pay and Associated Implicit Discount Rates

	*Mean Xiβ**	*Implicit r*
Rest of U.S.		
One Year Treatment	$121.50	
	(27.85)	
Five Year Treatment	132.30	-2.01
	(37.85)	
Fifteen Year Treatment	34.32	0.39
	(21.08)	
Rest of AK		
One Year Treatment	$67.07	
	(44.34)	
Five Year Treatment	38.71	1.36
	(38.05)	
Fifteen Year Treatment	-21.10	--
	(26.37)	
Boroughs		
One Year Treatment	-$137.90	
	(159.8)	
Five Year Treatment	-11.35	0.03
	(44.05)	
Fifteen Year Treatment	-31.46	0.29
	(41.88)	

Standard errors for WTP in parentheses.

Table 5: Estimation Results, Explicit Discount Rates for Three out of Six Treatments

	Rest of U.S. One vs. Fifteen	***Rest of AK One vs. Five***	***Rest of AK One vs. Fifteen***
ProSpec	162	312.5	385.8
	(54.65)	(150.3)	(233.4)
	2.965	2.079	1.653
ProJobs	-161.6	-122.6	-103.2
	(62.16)	(73.97)	(88.02)
	-2.599	-1.657	-1.173
KnowSSL	145.9	43.02	71.13
	(76.49)	(96.15)	(129.7)
	1.908	0.4475	0.5486
KnowVil	12.47	-102.1	-266.1
	(56.44)	(117.4)	(215.1)
	0.221	-0.8702	-1.237
Gender	90.39	137	195.8
	(62.59)	(106.8)	(158.5)
	1.444	1.283	1.235
Member	-128.9	-147	-222.5
	(102.4)	(132.9)	(196.)
	-1.259	-1.106	-1.135
Constant	-148.1	-646.1	-887.4
	(172.5)	(399.3)	(638.6)
	-0.8583	-1.618	-1.39
σ	235.4	369.3	474.1
	(71.46)	(171.1)	(277.8)
	3.294	2.158	1.707
r	0.4785	0.9247	-0.7438
	(1.18)	(2.725)	(.186)
	0.4056	0.3393	-4.005
Log Likelihood	-90.06	-123.4	-118.7

Standard errors in parentheses, followed by t-stats.

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